

# Matrix Factorization for Movie Recommendation Systems

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# Outline

1. Introduction to Recommendation Systems

# The Recommendation Problem

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**Think About It:**

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out of 15,000

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- Your friend has similar but different tastes
- How do we predict what you'll like?

|        |  | Users |   |   |
|--------|--|-------|---|---|
| Movies |  | ?     | ? | ? |
|        |  | ?     | ? | ? |
|        |  | ?     | ? | ? |

**Sparse Rating Matrix**





!

## The Magic Formula:

Alice's rating = Alice's preferences · Sholay's features

b Sholay's  
features:  $\mathbf{h}_1 = [0.95, 0.10, 0.85]^T$

$$\hat{a}_{11} = \mathbf{w}_1^T \mathbf{h}_1 \quad (1)$$

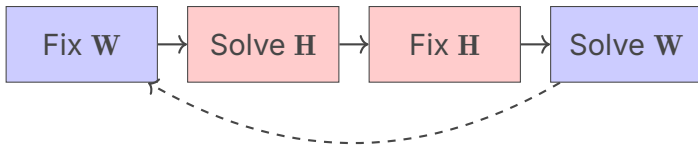
$$= w_{11} \cdot 0.95 + w_{12} \cdot 0.10 + w_{13} \cdot 0.85 \quad (2)$$

**Goal:** Find  $w_{11}, w_{12}, w_{13}$  such that  $\hat{a}_{11} \approx 5$  (Alice's actual rating)

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1.  $\mathbf{A} \in \mathbb{R}^{N \times M}$
2.  $\mathbf{W} \in \mathbb{R}^{N \times r}$
3.  $\mathbf{H} \in \mathbb{R}^{r \times M}$
4. Total parameters:  $Nr + rM = r(N + M)$

Initialize:  $\mathbf{W}^{(0)}$  and  $\mathbf{H}^{(0)}$  randomly



$$\text{minimize}_{\mathbf{w}_i} \sum_{j:(i,j) \in \Omega} (\mathbf{a}_{ij} - \mathbf{w}_i^T \mathbf{h}_j)^2$$

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**Matrix Form for User  $i$ :** Let  $\Omega_i = \{j : (i,j) \in \Omega\}$  (movies rated by user  $i$ )



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$$\mathbf{y}_i = [a_{i,j_1}, a_{i,j_2}, \dots, a_{i,j_{|\Omega_i|}}]^T \quad (3)$$

$$\mathbf{X}_i = [\mathbf{h}_{j_1}, \mathbf{h}_{j_2}, \dots, \mathbf{h}_{j_{|\Omega_i|}}]^T \quad (4)$$

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**Least Squares Solution:**

$$\boxed{\mathbf{w}_i^* = (\mathbf{X}_i^T \mathbf{X}_i)^{-1} \mathbf{X}_i^T \mathbf{y}_i}$$

$$\mathbf{y}_1 = \begin{bmatrix} 5 \\ 4 \\ 2 \\ 3 \\ 2 \end{bmatrix} \quad (5)$$

$$\mathbf{X}_1 = \begin{bmatrix} 0.95 & 0.10 & 0.85 \\ 1.00 & 0.20 & 0.90 \\ 0.05 & 0.80 & 0.30 \\ 0.05 & 0.95 & 0.70 \\ 0.05 & 0.15 & 0.95 \end{bmatrix} \quad (6)$$

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**Solution:**  $\mathbf{w}_1^* = (\mathbf{X}_1^T \mathbf{X}_1)^{-1} \mathbf{X}_1^T \mathbf{y}_1$

This gives us Alice's feature preferences!

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$$\mathbf{y}_j = [a_{i_1,j}, a_{i_2,j}, \dots, a_{i_{|\Omega_j|},j}]^T \quad (7)$$

$$\mathbf{X}_j = [\mathbf{w}_{i_1}, \mathbf{w}_{i_2}, \dots, \mathbf{w}_{i_{|\Omega_j|}}]^T \quad (8)$$

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## Objective Function:

$$L(\mathbf{W}, \mathbf{H}) = \sum_{(i,j) \in \Omega} (a_{ij} - \mathbf{w}_i^T \mathbf{h}_j)^2$$

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## Gradients:

$$\frac{\partial L}{\partial \mathbf{w}_i} = -2 \sum_{j: (i,j) \in \Omega} (a_{ij} - \mathbf{w}_i^T \mathbf{h}_j) \mathbf{h}_j \quad (9)$$

$$\frac{\partial L}{\partial \mathbf{h}_j} = -2 \sum_{i: (i,j) \in \Omega} (a_{ij} - \mathbf{w}_i^T \mathbf{h}_j) \mathbf{w}_i \quad (10)$$



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- One rating at a time
- Small adjustments
- Gradually improves

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3. **Update:**

$$\mathbf{w}_i \leftarrow \mathbf{w}_i + \alpha \cdot e_{ij} \cdot \mathbf{h}_j \quad (11)$$

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- If  $e_{ij} > 0$ : Predicted rating too low  $\rightarrow$  Increase similarity

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- If  $e_{ij} > 0$ : Predicted rating too low  $\rightarrow$  Increase similarity
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- Learning rate  $\alpha$  controls step size

Current:  $\mathbf{w}_1 = [0.4, 0.2, 0.3]$ ,  $\mathbf{h}_1 = [0.95, 0.10, 0.85]$  (13)

Prediction:  $\hat{a}_{11} = 0.4 \times 0.95 + 0.2 \times 0.10 + 0.3 \times 0.85 = 0.655$   
(14)

Error:  $e_{11} = 5 - 0.655 = 4.345$  (15)

$$\text{Current: } \mathbf{w}_1 = [0.4, 0.2, 0.3], \quad \mathbf{h}_1 = [0.95, 0.10, 0.85] \quad (13)$$

$$\text{Prediction: } \hat{a}_{11} = 0.4 \times 0.95 + 0.2 \times 0.10 + 0.3 \times 0.85 = 0.655 \quad (14)$$

$$\text{Error: } e_{11} = 5 - 0.655 = 4.345 \quad (15)$$

**Updates with  $\alpha = 0.01$ :**

$$\mathbf{w}_1 \leftarrow [0.4, 0.2, 0.3] + 0.01 \times 4.345 \times [0.95, 0.10, 0.85] \quad (16)$$

$$= [0.4413, 0.2043, 0.3369] \quad (17)$$

$$\mathbf{h}_1 \leftarrow [0.95, 0.10, 0.85] + 0.01 \times 4.345 \times [0.4, 0.2, 0.3] \quad (18)$$

$$= [0.9674, 0.1087, 0.8631] \quad (19)$$

!

**Answers:**



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$$\mathbf{X}_1 = \begin{bmatrix} 1.0 & 0.3 \\ 0.2 & 0.8 \end{bmatrix} \text{ (columns 1,3 of } \mathbf{H}^{(0)T} \text{)}$$

**Solve:**  $\mathbf{w}_1^{(1)} = (\mathbf{X}_1^T \mathbf{X}_1)^{-1} \mathbf{X}_1^T \mathbf{y}_1$

Continue for all users and movies...

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- Distributed computing, approximate algorithms, caching

matrix factorization can only work with explicit ratings

**Answers:**

stability requirements